Real-time machine learning: the next frontier?

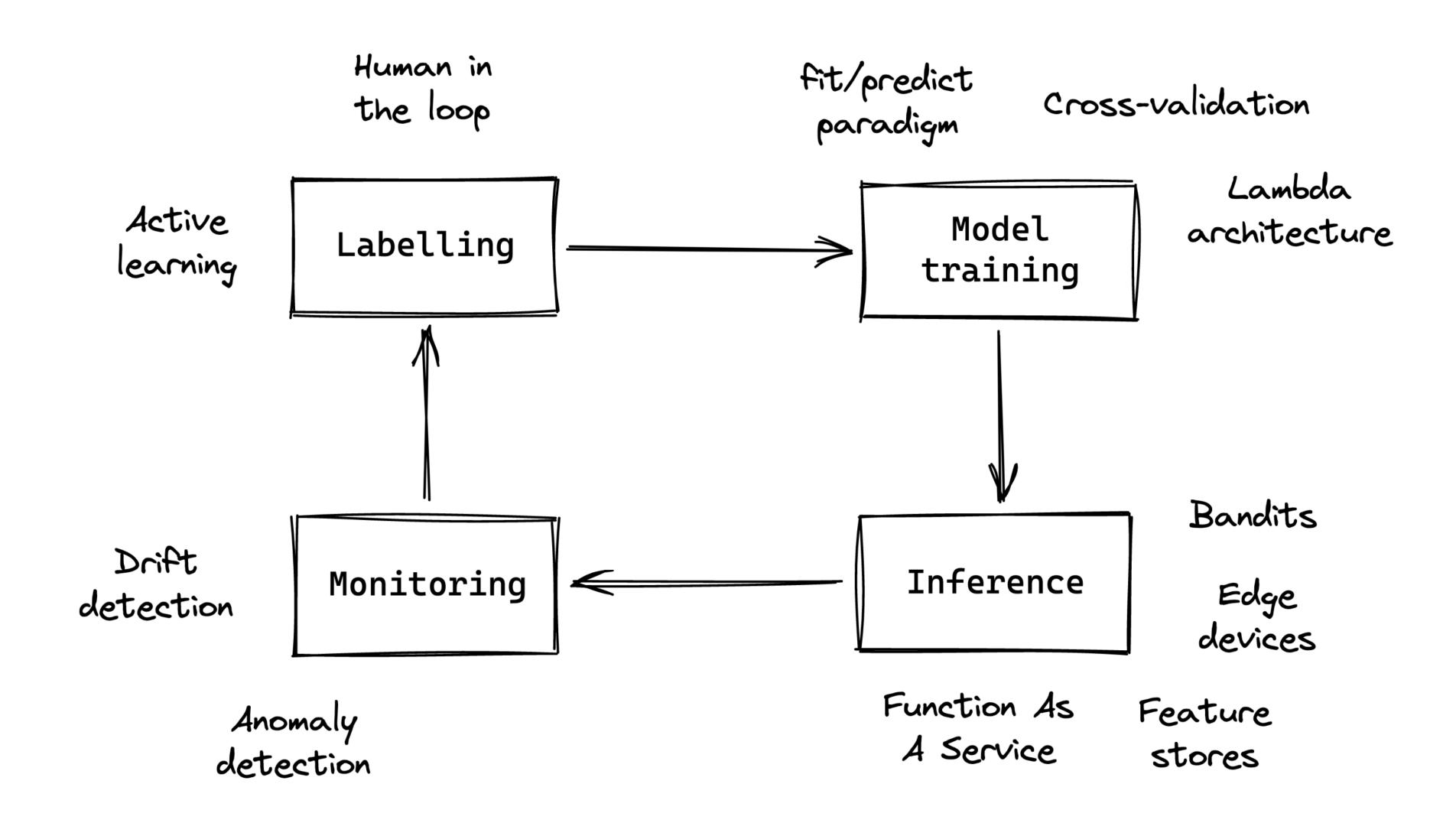
The Applied Al Community
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Hello, I'm Max!

- I enjoy all aspects of data
- PhD in query optimisation
- Kaggle competitions Master
- VI open source software
- ∠ I like to blog
- I'm a nomad



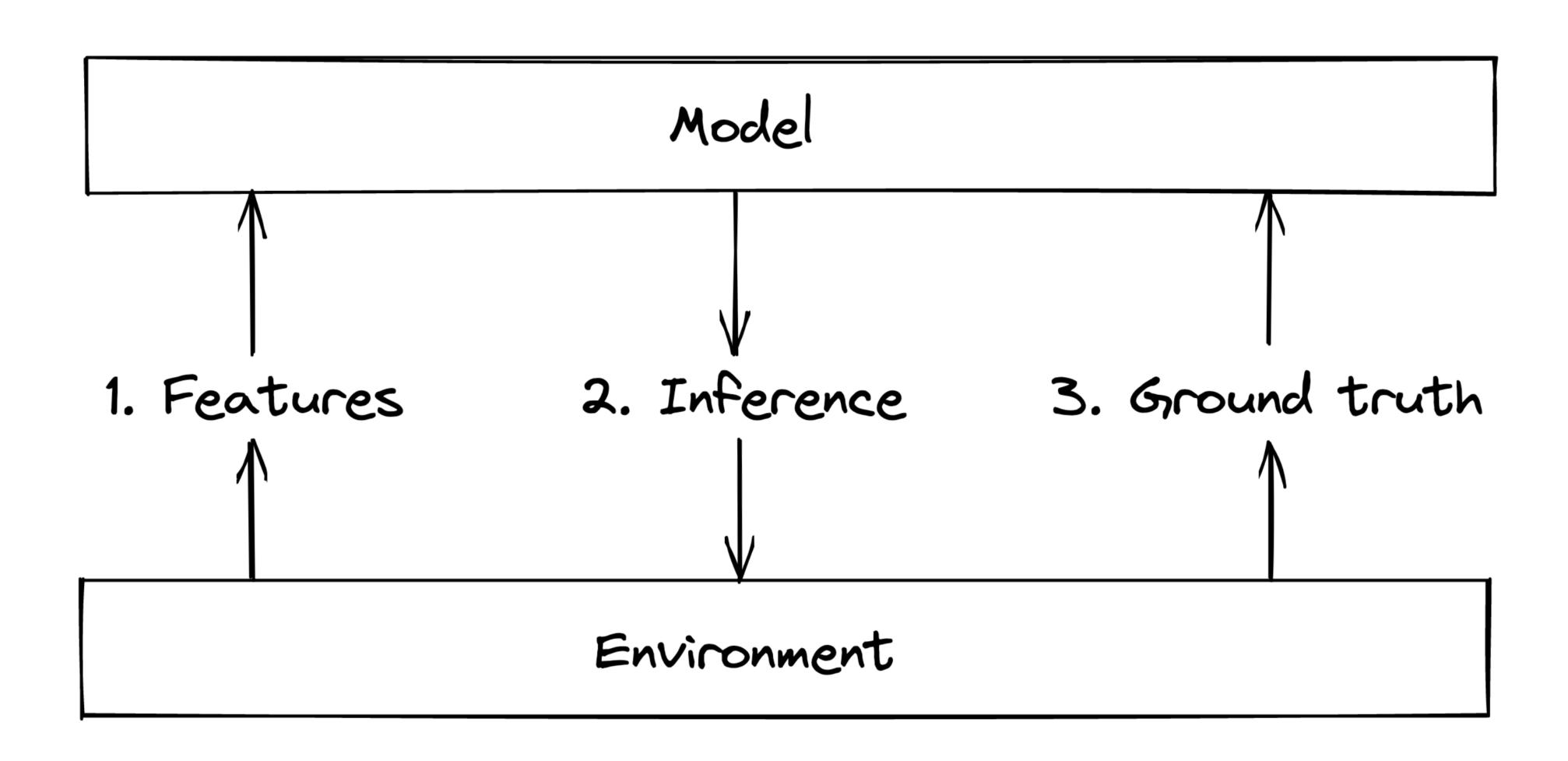
ML is maturing, design patterns are emerging



Batch learning is predominant

- Most ML models are batch models
- Batch models are trained on a static dataset
- Batch models have to be retrained from scratch
- Why is batch learning prevalent?
 - 1. It's what we're used to, it's comfortable
 - 2. It's taught at university
 - 3. Huge ecosystem

Models are static, but the real world is dynamic



Real-time inference ≠ learning

- Predictions are traditionally done in batch
- Some companies are getting better at real-time inference
- You can already do interesting things here:
 - Shadow deployments
 - Canary deployments
 - Bandits
- But this is different to real-time learning
- Real-time learning is more difficult
- Do you need it?

A growing need for real-time learning

- Netflix update recommendations in-session
- ** Trading learning as soon as possible gives an edge
- Mobility update routing from live traffic information
- Banking fraud patterns constantly evolve
- Sensors the definition of "normal" may change with time
- Cybersecurity hackers adapt to defence strategies
- ← Edge devices can't afford to store training data

"Real-time" is a weasel word

- There is no single definition
- Real-time means what you want it to mean
- Different applications will have different requirements
- You can fake it
- At the end of the day, what matters is the business impact

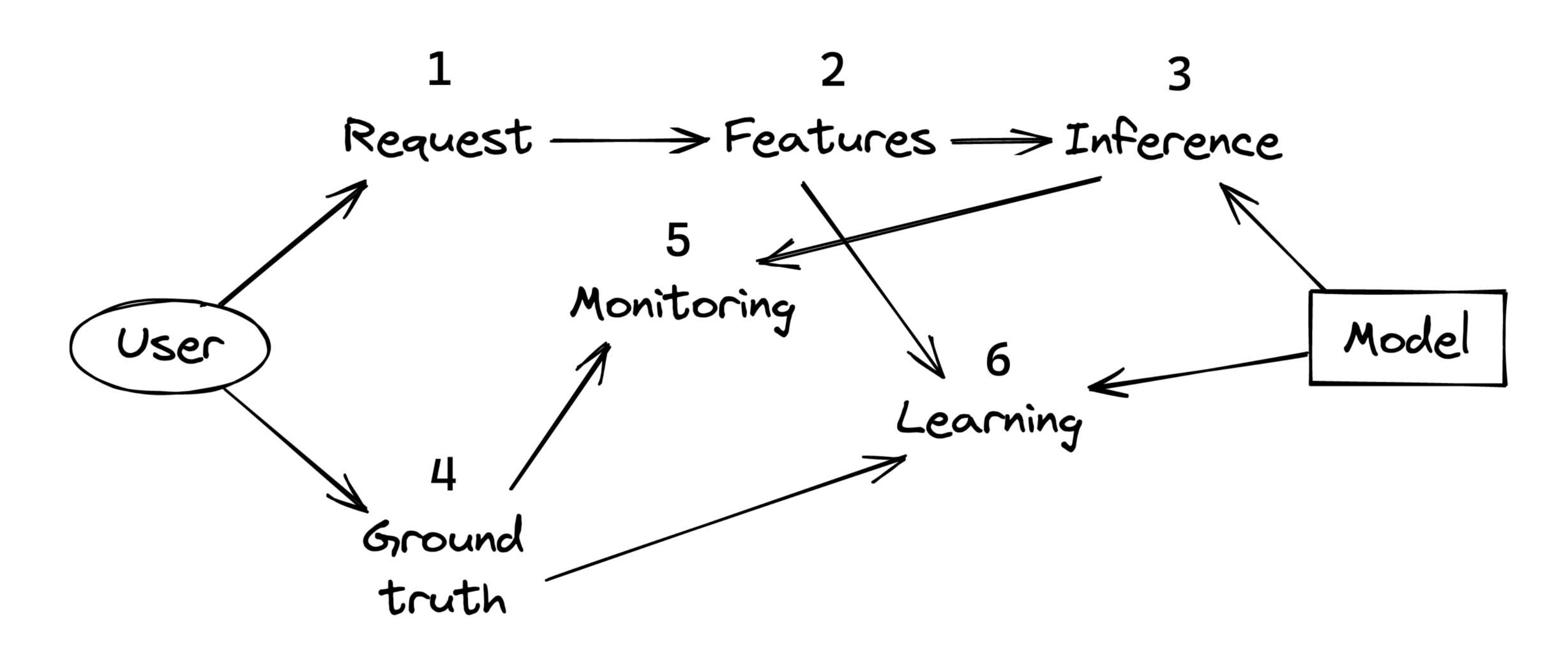
Batch retraining might be enough

- Usually, your system generates a stream of new training data
- Retrain your model periodically to cope with concept drift
- Maybe this works for you. If so, congrats
- There are some downsides:
 - It's wasteful
 - A schedule needs to be decided
 - Online/batch parity is not ensured

The alternative: online learning

- What if a model didn't have to be retrained from scratch?
- That's the mantra of online learning 🕹
- An online model can learn from one sample at a time
- It keeps on learning without having to revisit past data

The online learning lifecycle



The benefits

- lt's ecological because each sample is only seen twice
- The model is always up-to-date
- No training schedule is necessary
- Online/batch parity is ensured
- Backtesting is reliable
- Let teels like magic when it's running in production

Online/batch parity ©*

- How do you ensure features are available at inference time?
- Leakage is always possible, even if you use a feature store
- In an online fashion, you predict and then you fit
- You train with features that were available during inference
- Online/batch parity is ensured

See Building Faire's new marketplace infrastructure

Progressive validation



- Each data point (x, y) is used for inference and training
- First you predict, then you learn
- You can do an offline single pass over your dataset to
 - A. train your model.
 - B. obtain an out-of-fold score.

Delayed progressive validation

- You have control over the order in which the data is processed
- You can take into account the moment of arrival of x and y
- You can reproduce offline what happened online
- By doing this, you mimic production conditions
- This is closer to reality than cross-validation

See The correct way to evaluate online machine learning models

Stability-plasticity dilemma

- Plasticity integrating new knowledge
- Stability memorising previous knowledge
- Too much plasticity leads to catastrophic forgetting
- In an online setting, this might not be a problem
- Indeed, sometimes the goal is only to be good on recent data
- Continual/lifelong learning aims to address this dilemma

Why isn't online learning popular?

- Batch learning is pervasive
- It requires a different mindset
- It requires a more mature data platform
- The ecosystem is not as flowering as with batch learning
- We're missing some success stories



- 2 Python library for online machine learning
- Merger between creme and scikit-multiflow
- e I've been working on this for roughly ~3 years
 - ~26,000 lines of code, ~2,450 unit tests

Beginner's example

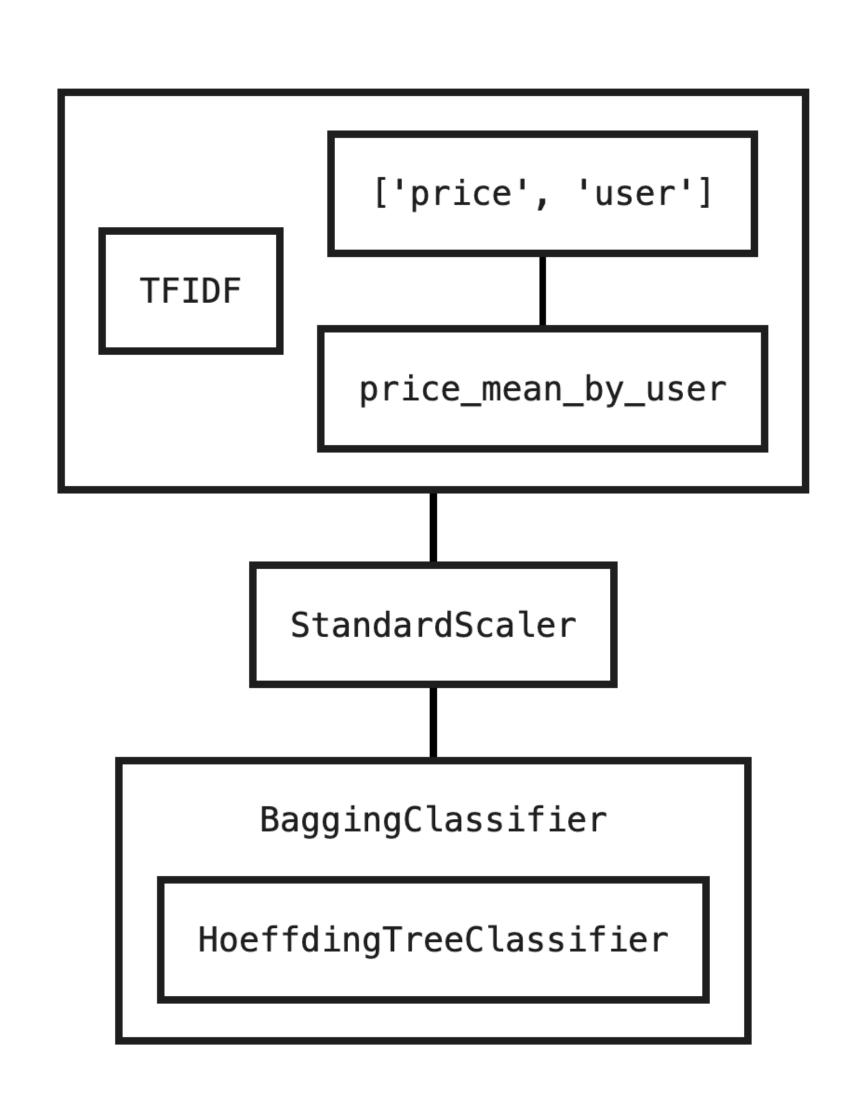
```
>>> from river import compose
>>> from river import linear_model
>>> from river import metrics
>>> from river import preprocessing
>>> model = compose.Pipeline(
       preprocessing.StandardScaler(),
       linear_model.LogisticRegression()
>>> metric = metrics.Accuracy()
>>> for x, y in dataset:
       y_pred = model.predict_one(x)  # make a prediction
       metric = metric.update(y, y_pred)
                                           # update the metric
       model = model.learn_one(x, y)
                                           # make the model learn
>>> metric
Accuracy: 89.20%
```

Plain dictionaries are the building blocks

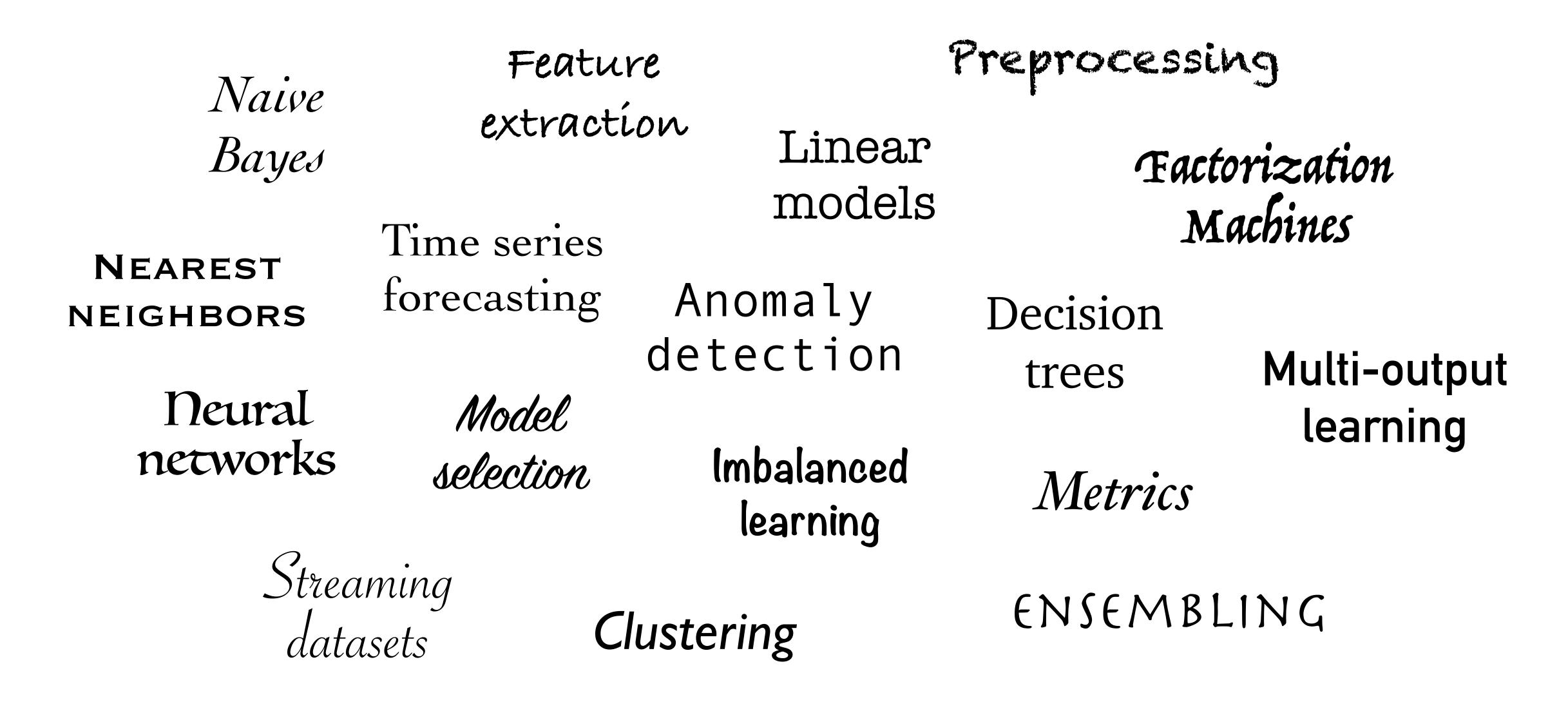
- Features are stored in dictionaries called "dicts" in Python
- Allow naming features
- Are to lists what pandas DataFrames are to numpy arrays
- Naturally represent sparse data
- Native to Python → no overhead like numpy/pandas/torch
- JSON-friendly

Pipelines are first-class citizens

```
>>> from river import *
>>> model = compose.Pipeline(
            feature_extraction.TFIDF(on='text') +
            compose.Pipeline(
                compose.Select('price', 'user'),
                feature_extraction.Agg(
                    on='price',
                    by='user',
                    how=stats.Mean()
        preprocessing.StandardScaler(),
        ensemble.BaggingClassifier(
            model=tree.HoeffdingTreeClassifier(),
            n_models=10
...)
>>> model
```



It's a general-purpose library



Speed considerations

- Many libraries implement SGD, which allows comparing them
- River is optimised for pure online learning single samples
- River shines when samples arrive one by one:
 - * 10x faster than Vowpal Wabbit
 - * 20x faster than scikit-learn
 - 50x faster than PyTorch
 - * 180x faster than Tensorflow

What about processing huge datasets?

- Sometimes, size matters.
- Learning with one sample at a time is not efficient
- To go big, vectorisation is necessary
- Some River models can process mini-batches
- In conjunction with <u>vaex</u>, you can process millions of rows per second
 - Pure online learning (i.e. individual samples) remains our main focus

Is it being used?

- Yes, it is!
- We know a couple of companies who use it production
- We've heard rumours of it being used for prototypes
- The amount of traffic and discussions on GitHub is steady
- We don't focus too much on fostering a widespread adoption
- Our goal is to satisfy the few teams who use River >>>

Our roadmap

- Our roadmap is public, see <u>here</u>
- Tentative areas of focus for 2022:
 - Online learning on graphs
 - Recommendation systems
 - Reinforcement learning
 - Anomaly detection
 - Comprehensive benchmarks
 - Delightful documentation

Feel welcome to make suggestions

Thinking beyond River

- River is "just" a machine learning library
- It's not an MLOps tool
- Deploying an online model requires some effort
- We see many people doing things differently
- There is an opportunity to standardise streaming MLOps
- That's my next endeavour 🍪

Takeaways

- Online machine learning isn't a one-size-fits-all solution
- Batch learning is perfectly adequate for many problems
- Use the right tool for the job!
- Online learning needs more success stories to see adoption
- We're friendly, so feel welcome to reach out 🥮

Further content

- Machine learning is going real-time Chip Huyen
- maxhalford.github.io/links#talks Yours truly
- One Pass ImageNet DeepMind
- Machine learning with Flink in Weibo Qian Yu
- Why TikTok made its user so obsessive? Catherine Wang

Thankyou

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